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An Exploration of ECG Signal Feature Selection and Classification using Mac hine Learning Techniques

M. Gowri Shankar, C. Ganesh Babu

Abstract*- This effort examines and likens a collection of active methods to dimensionally reduction and select salient features since the electrocardiogram database. ECG signal classification and feature selection plays a vital part in identifies of cardiac illness. An accurate ECG classification could be a difficult drawback. This effort also examines of ECG classification into arrhythmia kinds. This effort discusses the problems concerned in Classification ECG signal and exploration of ECG databases (MIT-BIH), pre-processing, dimensionally reduction, Feature selection techniques, classification and optimization techniques. Machine learning techniques give offers developed classification accurateness with imprecation of dimensionality.*

Keywords: *Feature Selection, Classification, Arrhythmia, MIT-BIH, Machine learning techniques*

I. INTRODUCTION

Cardio vascular diseases affect 17.9 million (estimated 31%) people worldwide every year. ECG Signal could be a medical examination that detects heart irregularity by through calculating the heart's electrical and muscle activity. A cardiac creates small electrical impulses that feast over cardiac muscle. Those impulses are often identified with ECG instrument. ECG instrument records the electrical action of the cardiac and shows this information on ECG graph sheet. That information is understood by a health care provider. ECG assistance to seek out the reasons for sign or heart pain and additionally helps to observe abnormal cardiac rhythm (heart defects). Usually healthy cardiac have a typical form. Some abnormalities with in the cardiac rhythm otherwise injury to the cardiac muscle will modification the electrical action of heart, therefore form of ECG signal gets modified. Clinician might suggest associate electro cardiogram for patients who might in danger of cardiac condition as a result of household history of heart condition, smoking etc. The cardiac disorders which will be detected using ECG take in irregular cardiac rhythm and distended heart.

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* Correspondence Author
M. Gowri Shankar*, Assistant Professor, Department of EEE, Gnanamani College of Technology, Namakkal, India. Email: mshankar065@gmail.com
Dr. C. Ganesh Babu, Professor, Department of ECE, Bannari Amman Institute of Technology, Sathyamangalam, India.

Electrocardiogram is one of the most effective cardiac illness diagnostic tools. Owing to high death rate of cardiac illness, initial recognition and accurate discernment of ECG signal stands important of the action of patients. Cardiogram signals classification exploitation optimized techniques will offer significant contribution to doctors to verify the diagnosing and recognition of heart illness sorts will facilitate classifying the abnormality of a patient.

When classifying the abnormality, the cardiac illness is noticed and therefore recovering treatment of the patient is done. Precise cardiogram classification into heart disease kinds offers enough info to recognition the cardiac illness. Classification of cardiogram signals is a difficult issue due to classification process problem.

Foremost classification of ECG problems, normalization of ECG features is lacking, changeability, originality, absence of best classification and inconsistency in graphs of patients. Emerging the foremost suitable classifier that's accomplished of classifying illness, ECG signal classifier main application is detect the cardiac illness diagnosis.

II. BACKGROUD KNOWLEDGE

The main function of ECG is heart's electrical and muscle activity. The electrodes mounted on skin are measured. It measures the pulse rate, rhythm as well as indirect evidence of blood flow to the heart muscle.

To generate twelve leads of electrical heart views, ten electrodes required. Twelve leads are,

1. Leads of the Limb – I, II, III
2. Leads of Augmented Limb – aVR, aVL, aVF
3. Leads of Precordial – V1, V2, V3, V4, V5, V6.

Heart contains 300 billion cardio myocytes. Cardio signal contains a quite lot of cardio beats, all cardio beat covers P wave, T wave and QRS Complex.

All peaks and intervals are PR, QRS, RR, QT and ST and Segments are ST and PR of cardio signals. It maintains the value of standard amplitude or interval. The above peaks, segments and intervals are entitled as features.

Figure.1. displays normal ECG wave and intervals [2]. Table.1, 2 below indicates the duration of the normal ECG waveform and also amplitude of the normal ECG waveform [4].

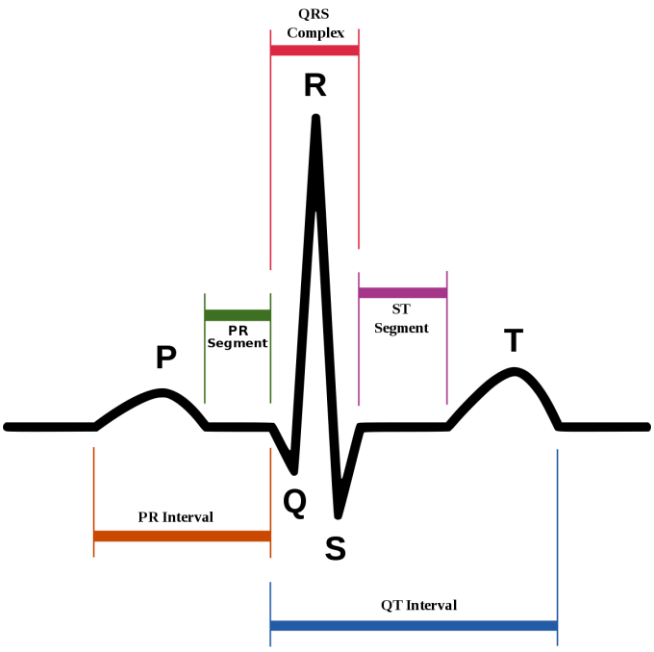

Figure.1. Normal ECG wave and Intervals [2]

Where, [2]
P - Atrial Depolarisation (<80ms)
QRS – Atrial Repolarization (<120ms)
T – Ventricular Repolarisation (160ms).
Graph Sheet – 0.1mv x 40ms
PR interval – 120-200ms

Table.1. Duration of ECG Normal Waveform Characteristics [4]

Feature	Duration in ms
P	80
QRS	<120
T	160
PR	120-200
RR	0.6-1.2 sec

Table.2. Amplitude of ECG Normal Waveform Characteristics [4]

Wave	Amplitude in mV
P	0.25
R	1.60
Q	25% of R
T	0.1 to 0.5

Figure.2. displays Einthoven's Triangle [3]. The below three leads (I, II, III) are voltage between positive electrode and negative electrode,

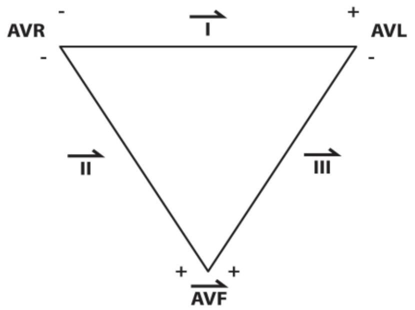

Figure.2. Einthoven's Triangle [3]

Where, [3] RL is electrode of earth.Lead of limb I is voltage between (LA – RA), lead of limb II is voltage between (LL – RA) and lead of limb III is voltage between (LL – LA). Cardiac signals classification is one of the important roles in cardiac illness medical diagnosis and drawback is diagnosing cardiac illness using electro cardiogram is normal signal vary for every person and occasionally single illness has different signs on dissimilar patients cardiogram signals. The above drawbacks complicate the cardiac illness diagnosis. So use of classifier techniques can develop the new patient's cardiac arrhythmia diagnosis. Cardiac arrhythmia is a category of disorders where the heart beat is too fast otherwise too slow irregular (>120 beats/min – Tachycardia, <60 beats/min – Bradycardia). Table.3. displays the detailed exploration of classification arrhythmia.

III. MATERIALS AND METHODS

In this effort ECG classification consist of six blocks

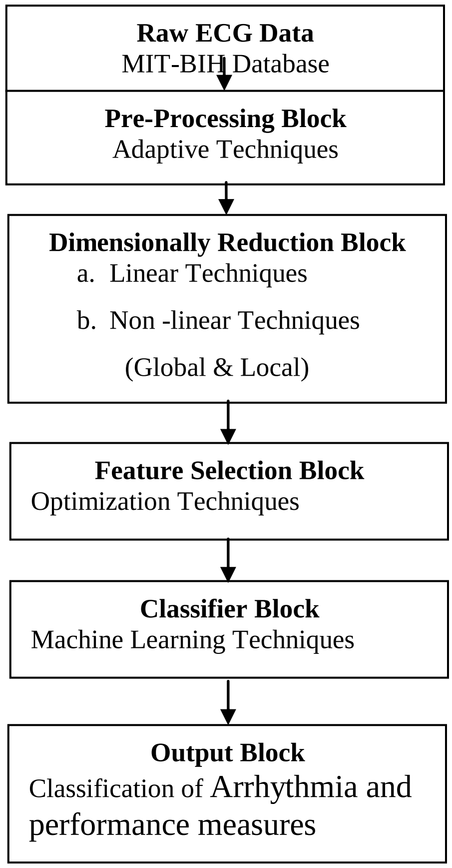

Figure.3. Flow Diagram of ECG Data Classification

A. Data Block:

Many investigators used Arrhythmia Database of MIT-BIH. It comprises 48 subjects; the length of each subject is 30 minutes and the range of band pass filter exists 0.1HZ to 100 HZ. Sample rate of frequency of database is 360HZ. The MIT-BIH database is 11 bit resolution over 10 mv range and total beat labels is 110109. This consists of various leads, such as having 45 files in MLII, 40 files in V1 and 11 files in II, V2, V4 and V5. Timing information and beat classification are annotated in the database.

The sample data available at Physio Bank service [31].

B. Pre-processing Block:

Filtering was used to pre-process the cardiac signals. High-frequency noise and low-frequency noise should be eliminated. Different kinds of noise affect cardiac signals for example high frequency noise include electromyogram noise, white Gaussian additive noise, power line interference and low frequency noise include baseline wandering. [6]. Many investigators had applied different noise removal (pre-processing) techniques such as wavelet transform based technique, curvelet transform based technique and Adaptive digital filters. Thakor and Zhu [32] had done the noise removal by a digital filter using continuous otherwise unity reference input. That was used to remove low frequency noise. Yet, this type of filter isn't consistent for applications that require diagnostic ECG analysis.

C.Dimensionally Reduction Block:

The necessary function for the selected classifier with the help of the relevant dimension reduction technique and it is very vital task in machine learning techniques. Most of the investigators used reduction techniques such as linear techniques (PCA and LDA), global nonlinear techniques (MDS, SNE, GDA, Kernel PCA, Diffusion Maps, Fast MVU, ISOMAP and Multilayer Encoder) and local nonlinear techniques (LLE, Hessian LLE, LTSA and Laplacian Eignmaps). These are all majorly used in dimensionality reduction techniques [33].

D.Feature Selection Block:

Supervised Optimized techniques are preferred for its selection. Features are classified into two groups (i) Morphological features and (ii) statistical features. The morphological features such as intervals are QRS, T, and P, amplitudes are R, R & S, P & T and delineation intervals are QRS, T, P, RR and ST slope. Statistical features such as Variance, Mean, Skewness, Standard deviation, Spectral entropy and Kurtosis. For selection of features techniques are follows Genetic Algorithm (GA), Grey Wolf Optimizer (GWO) and Particle Swarm Optimization (PSO).

E. Classifier and Optimizer Block:

Supervised machine learning techniques is preferred for its generalization. For classifier techniques such as Artificial bee colony optimized least square twin support vector machine (ABS-LSSVM), Probabilistic Neural Network (PNN), Support Vector Machine (SVM), Multilayer Perception (MLP), Radial Basis Function Neural Network (RBFNN), Cuckoo Search, Selecting Base Classifiers on Bagging (SBCB), Moving Linear Regression (MLR), Singular Valued Decomposition (SVD), Feed Forward Neural Network (FFNN) and Quantum Neural Network (QNN).

F. Output Block:

Give the performance measures and result of heart disease diagnosis. Performance measures are specificity (Sp), sensitivity (Se), Accuracy (A), positive predictivity value (PPV) or precision and error beats (E). Their relevant descriptions using true positive rate (TPR), false positive rate (FPR) or called fallout, true negative rate (TNR) and false negative rate (FNR) or Miss, these all are achieved from the results of the classification as follows [34]:

- Se =True positive/(True positive + False negative) * 100;
- Sp =True negative/(True negative + False positive) * 100;
- Fallout =False positive/(True Negative + False positive)* 100;
- Miss =False negative/(True positive + False negative)*100;
- Precision =True positive/(True positive + False negative)* 100;
- A = True positive + True negative / (True positive + False negative + False positive + True negative) * 100;
- E = False negative + False positive;

IV. RESULT ANALYSIS AND DISCUSSION

In this section we described results of two blocks (i) pre-processing block and (ii) dimensionally reduction block and exploration of ECG signal classification. Signals of normal and cardiac arrhythmia are extracted from the MIT-BIH database. In this pre signal processing block, simple approach to power line interference reduction is to consider a filter identified by a complex-conjugated pair of zeros at the interfering frequency in the unit circle. Implements (Matlab) the two IIR (notch) filters, one to eliminate the low frequency noise with 0.68 Hertz and another one eliminate the high frequency noise with 50 Hertz. The results of the pre-processing block displays in figure.4.

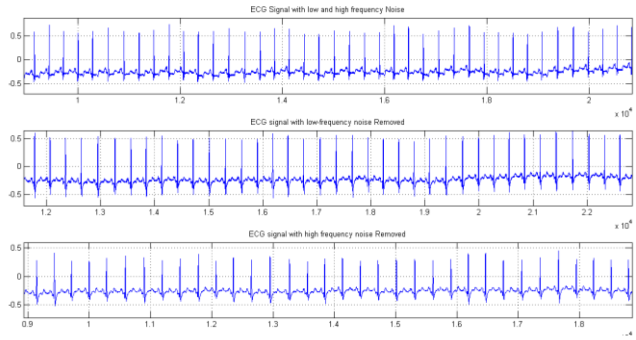

Figure.4. Simulation result of ECG signal with low and high frequency noise, ECG signal with low frequency noise removed and ECG signal with high frequency noise removed.

In this dimensionally reduction block, linear and non-linear approach to high dimensional data to low dimensional reduction data reduction is to consider linear technique and non-linear technique. Advantage of linear technique is simple geometric representation and desirable computing properties and advantage of non-linear technique is sparse matrix used so computational efficiency high and polynomial speedup. Samples are divided into equal sets, 80% of training and 10% of testing. High dimensional data displays in figure.5 using matlab, results of dimensionally reduction displays in figure.6 using linear technique and results of dimensionally reduction displays in figure.7 using Non- linear technique.

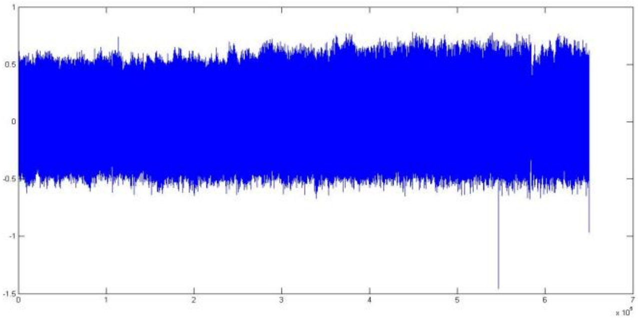

Figure.5. Simulation result of High dimensional ECG data

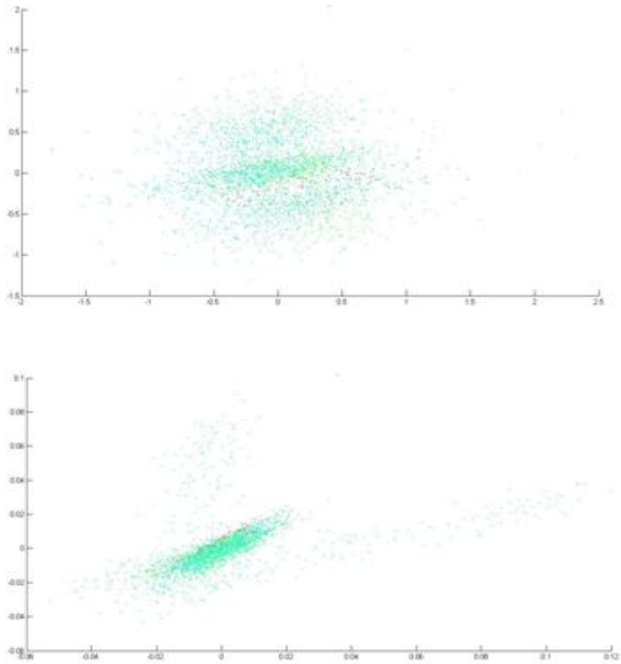

Figure.6. Dimensionality reduction using linear techniques

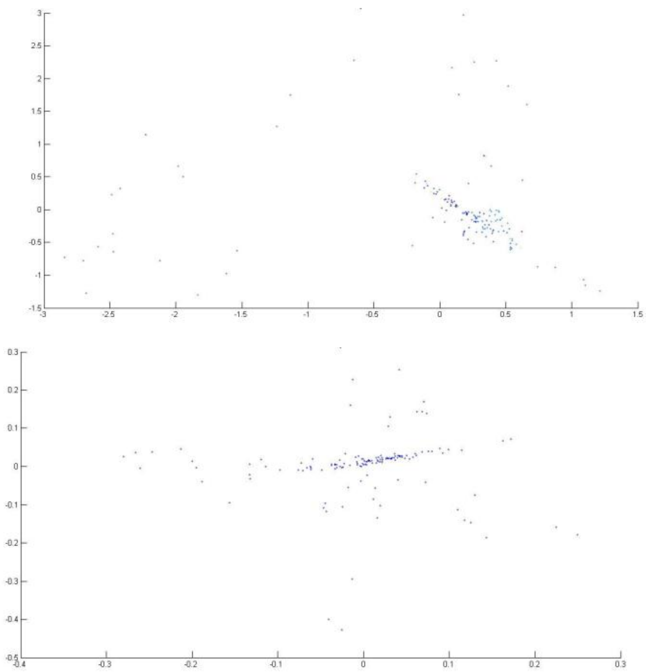

Figure.7. Dimensionality reduction using Non- linear techniques

Several investigators have analyzed the classification of ECG signals and have applied various techniques of pre-processing, several techniques of dimension reduction, feature selection techniques, classifiers and also several investigators used the ECG Signal Classification database for MIT-BIH arrhythmia.

Mehdi Ayer, Saeed Sabamoniri [7], have selection of feature and heart beat classification using genetic algorithm with decision tree. The performance measures are accuracy 86.96%, Sensitivity 88.88%, and Sen-Spec metrics 85.55%. F. Bereksi Reguig, N.Belgacem and M.A.chikh, [8], two supervised neural networks used to classification of ECG signals. The first neural network is MLPNN, performance measures are 89% of correct classification, 88.17% of Specificity and 92.17% of Sensitivity. The second neural network is LVQNN, performance measures are 91.55% of correct classification, 94% of Specificity and 94.24% of Sensitivity. Yun-Chi Yeh, Liuh-Chii Lin and Tsui-Yao Chu [9], Analysed selection of feature and heart beat determining of ECG signals. Feature selection using principal component analysing and heart beat determination carried out Fishers LDA and fuzzy logic. Performance measures show the total classification accuracy 94.03% and 93.87%. Exploration of electro cardiogram Signal Classification presented in table.4.

Table.3. Exploration of Arrhythmia Classification

Conditions	Rhythm Regularity	Heart Beat Rate	P-Wave	P-R Interval	QRS width
SA Node Arrhythmia					
Sinus Bradycardia	Regularity	<60 bpm	Present in ECG waveform	Mostly Normal. If present P wave then would be 120-200 ms	<120/ <100 ms
Sinus Tachycardia	Regularity	>100/ >120 bpm	Present in ECG waveform	Mostly Normal. If present P wave then would be 120-200 ms	<120/ <100 ms
Sinus Arrest/ Sinus Pause (failure of impulse delivered from SA node)	Regular & irregular during sinus arrest	Normal	Regular: Normal Shaped Size Irregular: During Sinus Arrest P wave will be absent	P wave normal, PR interval measured. P not present PR cannot be measured	If P wave present QRS normal, else QRS can't be measured.
Sinus Block impulse delivered from SA node but blocked before reading AV node	Regular & irregular during sinus block	Normal	Regular: Normal Shaped and Size follows QRS Irregular: During Sinus Arrest Block	P wave normal, PR interval measured. P not present PR cannot be measured	If P wave present QRS normal, else QRS can't be measured.
Atrial Arrhythmia					
Wandering Atrial pacemaker generating a pulse anywhere inside the heart SA atria/ AV node	Regular	60 to 100 bpm	May vary in shape, size and direction	May vary it depends upon the ectopic site shifted.	<120/ <100 ms
Premature Atrial contraction occurs in stress, emotions and drugs. If continuous leads to serious atrial arrhythmia	Regular/ irregular during PAC	One fast beat during PAC or normal	An abnormal shape, size and direction of premature P wave. Hidden at times in the previous wave of T.	Normal / prolonged PR interval	Normal but sometimes occurs premature
Atrial Tachycardia	Regular	AR = 140 to 250 bpm VR=140 to 250 bpm	An Abnormal and can be hidden in QRS/ T wave	Normal but not measureable	<120/ <100 ms
Atrial Flutter	Regular/ irregular depends upon AV conduction ratio	AR = 140 to 250 bpm VR=varying	Abnormal/ saw tooth/ V shaped	Not measureable	Normal
Atrial Fibrillation	Grossly irregular, rarely regular	AR = 350 to 450 bpm VR=Varying	Fibrillatory waves present	Not measureable	Normal
AV Junctional Arrhythmia					
Junctional escape rhythm SA node impulse failed to reach AV node then a transient rhythm generated from AV node	Regular/ Irregular	40 to 60 bpm	Inverted before/ after during QRS	Short	<120/ <100 ms
Premature Junctional Contraction	Regular/ Irregular during PJC	Underlying Rhythm / Natural	Inverted before/ after/ during QRS can be hidden in QRS	Short	Normal/ Narrow
Acceleration of Junctional Rhythm	Regular/ Irregular	60 to 100 bpm	Inverted before/ after during QRS	Short	Normal
Paroxysmal Junctional Tachycardia	Regular/ Irregular during PJT	Underlying Rhythm	Inverted before/ after during QRS may be hidden in QRS	Short	Normal/ Narrow
Ventricular Arrhythmia					
Premature Ventricular Contraction	Regular/ irregular during PVC	Underlying sinus rhythm	Normal: sinus rate Irregular: No P wave associated with QRS	Not applicable	Premature, broad and wide >120ms varying shape and size
Ventricular Tachycardia	Regular/ may be irregular during VT	140 to 250 bpm	Normal: sinus rate Irregular: No P wave associated with QRS	Not applicable	Premature, broad and wide >120ms varying shape and size
Ventricular Fibrillation	Chaotic	Can't be measured	Absent	Not applicable	Absent

Table.4. Exploration of Electro Cardiogram Signal Classification

Model of Classifier	Characteristics	Performance Metrics
GA with DT [7]	It have feature selection and heart beat classification	Accuracy 86.96% Sensitivity 88.88% Sen-spec metrics 85.55%
MLPNN based LVQ [8]	It is two supervised two neural networks are used. It is classifying the ECG signals.	**MLPNN:** Correct Classification 89% Specificity 88.17% Sensitivity 92.17% **LVQNN** Correct Classification 91.5% Specificity 94% Sensitivity 94.24%
Fuzzy logic [9]	Feature Selection carried out and also heart beat determination carried out fishers LDA with Fuzzy Logic	Accuracy 94.03%
FFNN based SVM, DWT-MLPNN, CWT-MLPNN [10]	Pre-Processing, Feature Selection using wavelet transform are DWT, CWT, DCT	**MSE** 0.0349 0.0438 0.0056 0.1048
RBFNN classifier RBFNN parameters PSO-RBFNN [11]	Pre-processing carried out median filter and Low pass linear phase filter , selection of feature carried out PT algorithm	Sensitivity 96.251 Specificity 99.104
MLPNN with BPA K-A algorithm based SVM [12]	R to R interval detection and baseline wandering removal	**MSE** 0.007656 0.1539 04:45
Hybrid NN Model [13]	Hybrid NN model obtained precision rates greater than the stand-alone neural network model.	Accuracy 96.94%
MLPNN [14]	Pre-processing, Feature selection carried out.	Accuracy 97.78%
ICA with BPNN [15]	Multi resolution analysis and neural network	Accuracy 98.37%
PSO with SVM [14]	Morphology feature selection , pre-processing wavelets	Accuracy 91.67%
HSO with SVM [16]	Different kind of pre-processing processes used to improve the overall accuracy of ECG recognition.	Accuracy 94%
Adaptive Neuro Fuzzy [17]	Pre-processing carried out Classifier is Adaptive Neuro-Fuzzy Inference System	Accuracy 93%
SVM invariants [18]	Pre-processing, feature selection and Arrhythmia Classification carried out	Accuracy 81.11%
GABC based Neuro-fuzzy classifier [19]	Carried out hybrid feature classification.	Accuracy 93%
ABC-LSTSVM [20]	DOST based ABC-LSTSVM techniques. Pre-processing median Filter Used	Accuracy 96.29% & 86.89%
Using a modified rule-based method SVM and SRC [21]	Classification based on representation is incomplete. It is the classification of myocardial ischemia	SRC 96.26%
HRV feature extraction with SVM [22]	Pre-processing and Feature extraction carried out.	Accuracy 96%
ELM [23]	It can be classified normal and abnormal signal ELM compared with SVM.	Overall Accuracy 89.74%
ALO [24]	It is carried out feature selection compared with PSO and GA. ALO is good searching capability.	High
GA with Multi objective approach [25]	It is feature selected for heart beat determination	Accuracy 98.79%
FFNN (four layer) classifier and fuzzy classifier [26]	Feature extraction carried out Pan- Tompkins algorithm.	Accuracy 80-85%
Cascade FFNN with BPNN algorithm [27]	Pre-processing and feature selection carried out.	MSE 0.00621
MLPNN with error BPNN algorithm [28]	Pre-processing- wavelet transform technique carried out.	Accuracy 96%
MLPNN with SVM and RBFNN Classifier combined with PCA, PCA with SVM, DCT with RBF, DCT with SVM, DWT with RBF and DWT with SVM [29]	Dimensionally reduction using PCA, DWT , Feature Selection Using PT algorithm	Accuracy 99.55%
Genetic Algorithm with ICA (GICA) [30]	Pre-processing: Wavelet transform technique Dimensionality Reduction: PCA Feature Extraction: ICA Classifiers: GA with SVM and ICA	Specificity 92.5% Sensitivity 94% Accuracy 93.33%

All of these are critical and crucial measures for determining overall system performance and medical diagnosis [34].

The above exploration of feature selection methodologies with various Optimization technique classifiers is used to point out and classify normal and different Cardiac Arrhythmias like:

Normal Sinus Rhythm (N), Sinus Bradycardia (SBR), Atrial Fibrillation (AFIB), Ventricular Tachycardia (VT), Idioventricular Rhythm (IVR), Ventricular Flutter (VFL), Myocardial Infarction (MI), Premature Ventricular Contraction (PVC), Supra Ventricular Tachycardia (SVT), ST Deviation (ST), Ischemia Change (LT), Myocardial Ventricular Arrhythmia (MVA), Atrial Flutter.

V. CONCLUSION

This effort showing a relative table estimating the performance of various algorithms that was carried out before the ECG signal classification and machine learning technique area of those classifiers is also shown in Table.4. This feature selection is done in completely involuntary technique. These results show that, the different classification system significantly improves the detailed fitness attained by the various classifiers and it is heftiness against the issue of limited availability of training beat that may characterize unusual occurrence pathologies. Refining the accurateness of analyzing the heart illness in advance is important with in the case of human monitoring system. So, forthcoming efforts can extend the diagnosis accuracy of the heart illness. All of those approaches can offer information to the person who reads about the finest signal pre-processor block, dimensionally reduction block, feature selector block and classifier block machine learning techniques aimed at arrhythmia classification.

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AUTHORS PROFILE

Mr. M. Gowri Shankar, received his B.E (EEE) degree from Mahendra Engineering College, Tiruchengode in 2012. He obtained his M.E (VLSI Design) degree from MIET Engineering College, Trichy in 2014. He has five years teaching experience at college level. He is pursuing his doctoral research programme as a research scholar (QIP, Pre-Ph.D period, IIT Delhi) in Bio signal processing under guidance of Dr. C. Ganesh Babu at Department of ECE, Bannari Amman Institute of Technology Sathyamangalam. Currently he is working as Assistant Professor in Department EEE at Gnanamani College of Technology, Namakkal. His area of interest is Bio Signal Processing and VLSI Design. He is member of IAENG.

Dr. C. Ganesh Babu, received his B.E (ECE) degree from PSG College of Technology Coimbatore in 1994. He obtained his M.E (Microwave and Optical Engineering) degree from Allagapa Chettiar College of Engineering and Technology, Karaikudi in 1997. He was awarded Ph.D. in I&C Engg from Anna University, Chennai in 2010. He has 22 years of teaching experience at college level. He was Assistant Professor in ECE at Sri Krishna College of Engineering and Technology, Coimbatore. Currently he is working as Professor ECE at Bannari Amman Institute of Technology, Sathyamangalam. Two scholars have completed their doctoral degree under his guidance and seven scholars are continuing currently. He has published thirty eight papers in International and National Journals and also published around fifty seven papers in International and National Conferences conducted both in India and abroad. His area of interest is Signal Processing, Virtual Instrumentation. He is life member of IETE, IET and ISTE.